Progress Towards Machine Learning-Based Real-Time Non-Destructive Prediction of the Longitudinal Phase Space Evolution in a Particle Accelerator

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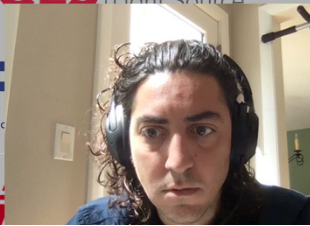
Virtual

U.S. DEPARTMENT OF ENERGY
Office of Science

LCLS Linac Coherent



A.L. Edelen et al IPAC 201

Virtual diagnostics

Predict what the output of a diagnostic would look like when it is unavailable

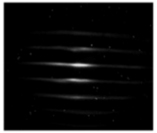
Fast physics-based simulation

ML model

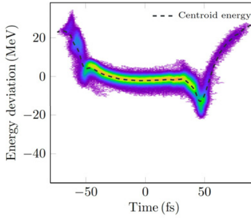
"Real-time" prediction of beam characteristics or explicit diagnos output

Measured machine inputs (non-destructive)

Virtual diagnostic



$\epsilon_y, \langle y^2 \rangle, \langle yy' \rangle, \langle y'^2 \rangle$



Challenges with physics-based simulation approach:

Execution often still isn't so fast (sec-mins)

Can require HPC resources

Often takes much effort to replicate machine behavior!
(And even then, need to account for drifts)

Another approach:
Use a ML model

Once trained, neural networks can execute very quickly

Train on data from slow, high fidelity simulations
+
Train on measured data

Virtual diagnostics

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Virtual diagnostic

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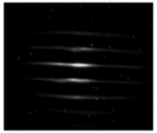

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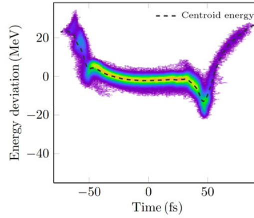

Challenges with physics-based simulation a

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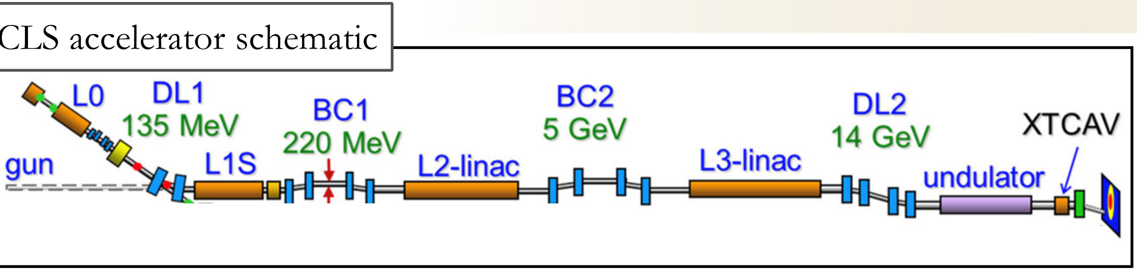
Joint benefits:

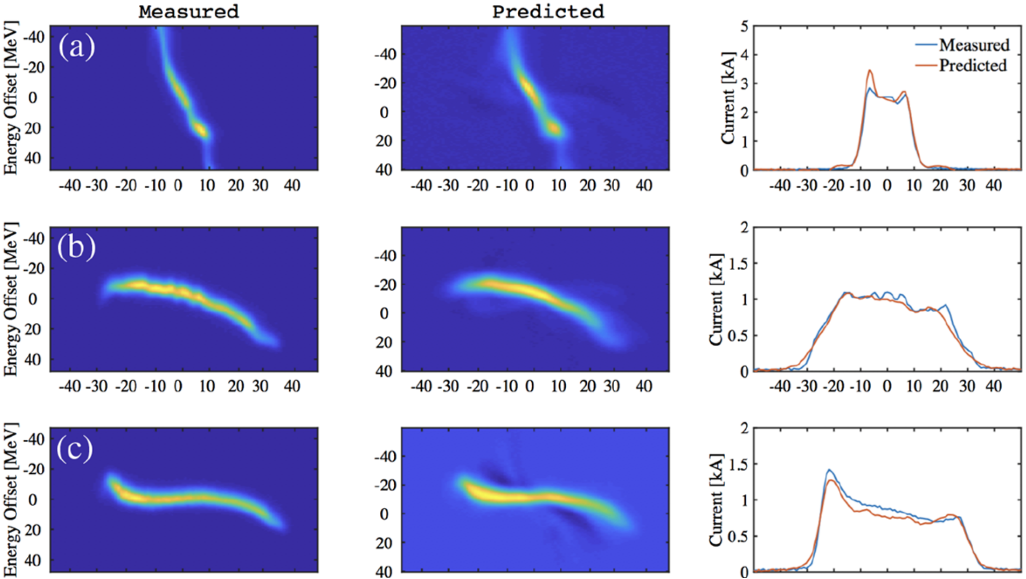
Additional information for user experiments

Additional signal to feedback on for LPS tuning

LCLS experimental proof of concept

SLAC





LCLS Experiment:

Machine parameters scanned:
L1s phase from -21 to -27.8 deg

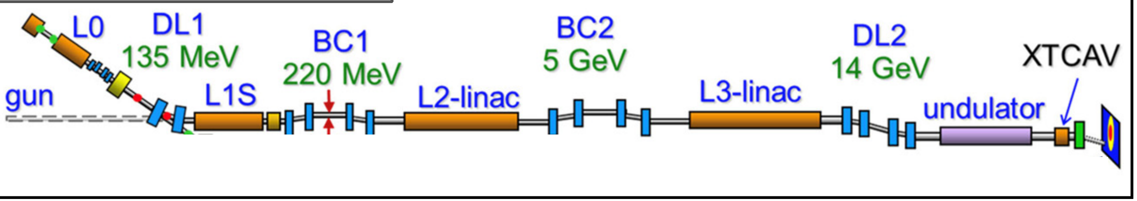
BC2 peak current from 1 to 7 kA

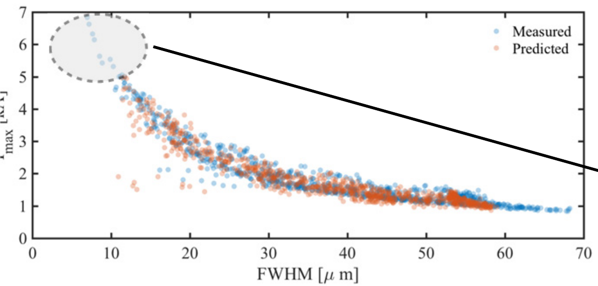
Inputs to ML model:
L1s voltage & phase readbacks,
L1x voltage, BC1 and BC2 current

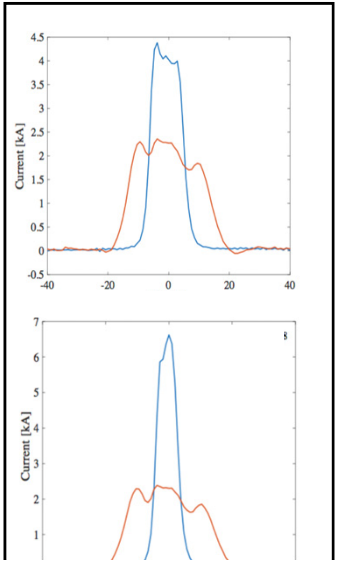
- ML prediction of LPS/current profile from **fiv** scalar inputs agrees well with measurement

LCLS experimental proof of concept

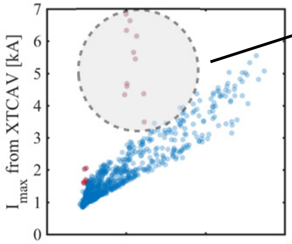
CLS accelerator schematic







Shots with
'bad' prediction
circled



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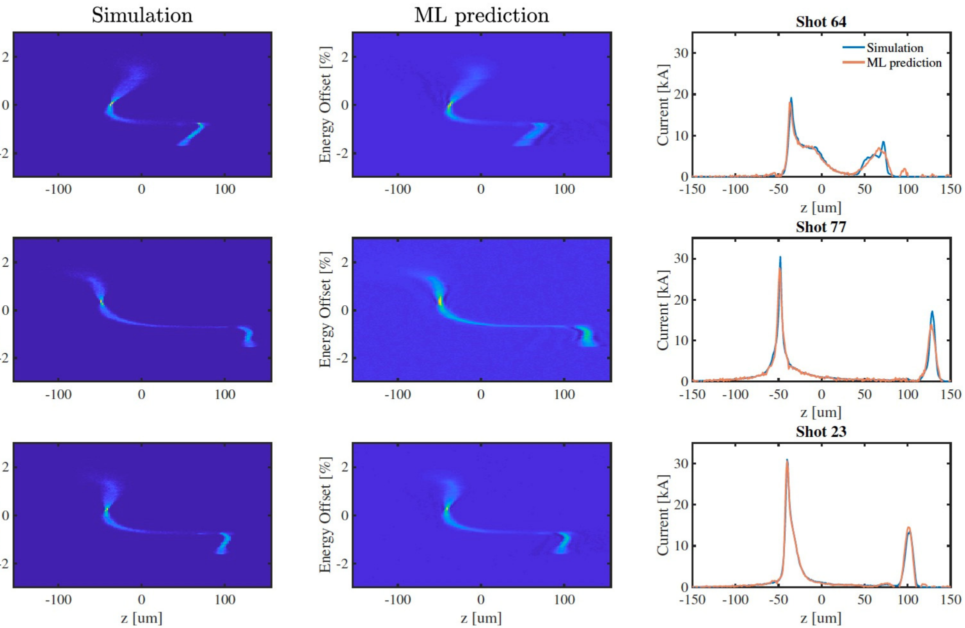
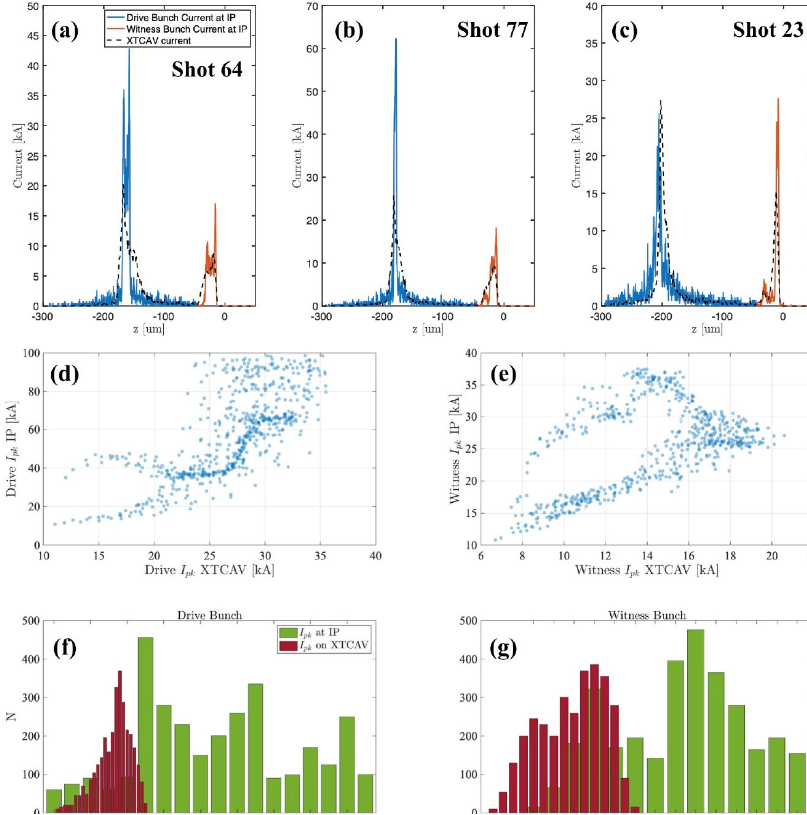
- ML prediction of LPS/current profile from **fiv** scalar inputs agrees well with measurement
- Bad predictions can result from large discrepancy between diagnostic input (e.g. BC2 current) and XTCAV current (see bad shots).
- Flagging bad shots (e.g. with redundant diagnostic) is important for trusting virtual

FACET-II simulation study

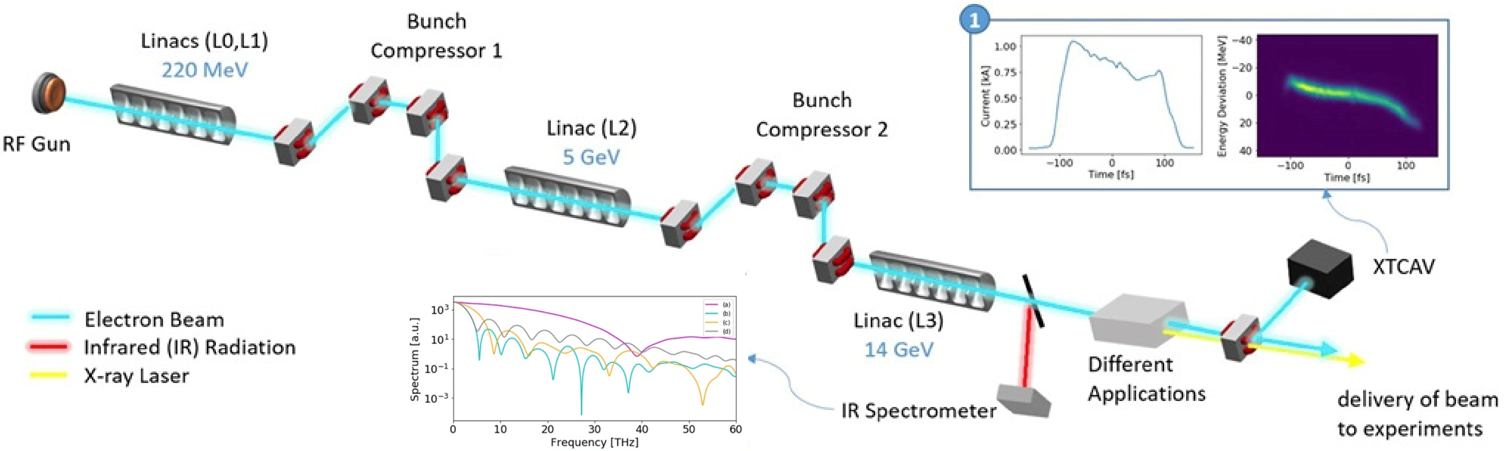


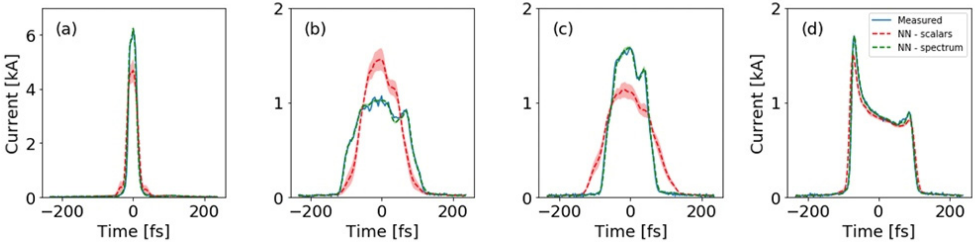


LPS features (rel. chirp, time & energy separation) can be predicted with ML diagnostic

Resolution is limited to ~ 4.5 um or I_{pk} = 35 kA due to limited

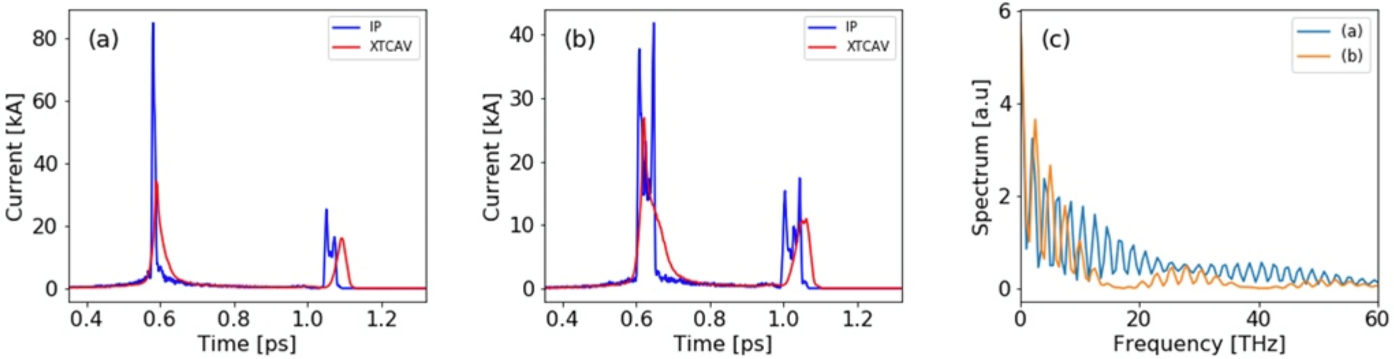
Increased prediction accuracy with spectral data

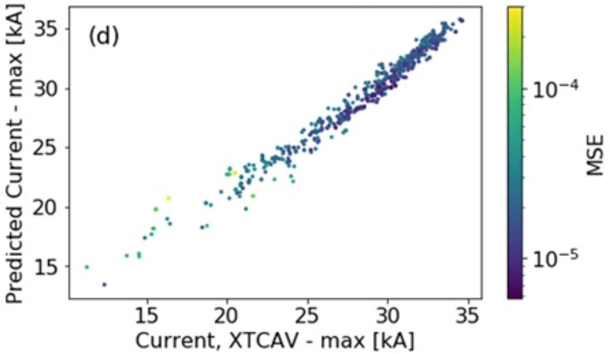




Adding spectral input improves accuracy of ML diagnostic prediction

Increased prediction confidence with spectral data



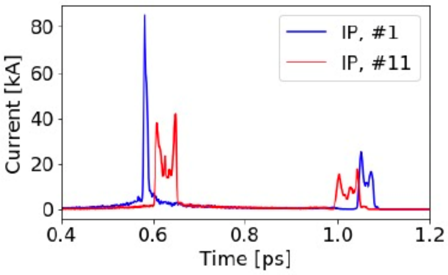


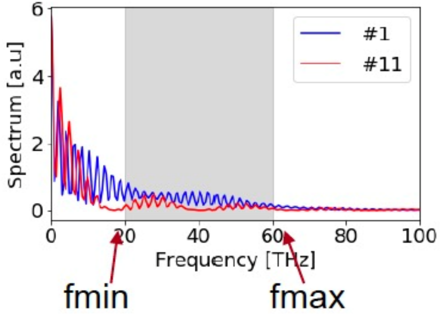
High peak current at the IP will be smeared on the TCAV, but spectrum is different!

↓

Train spectral VD to predict current based on TCAV.

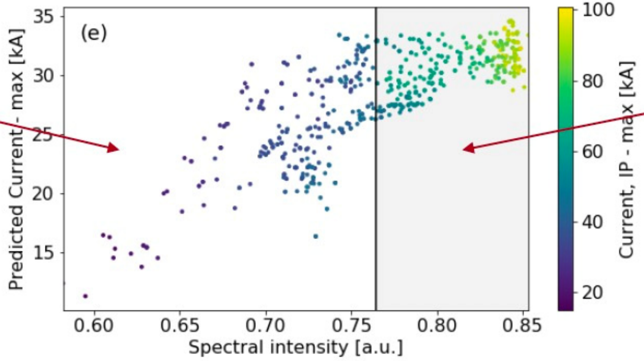
Spectral virtual diagnostics for increased confidence





Optimize the frequency band to distinguish between high peak current (>35 kA) shots to lower ones.

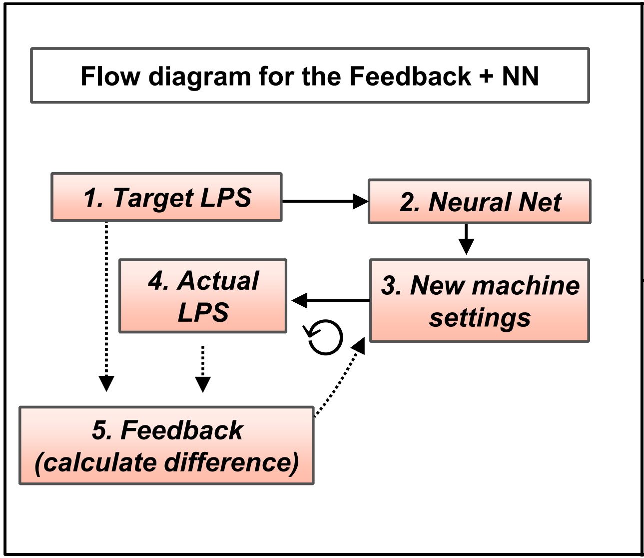
High confidence region (46%)

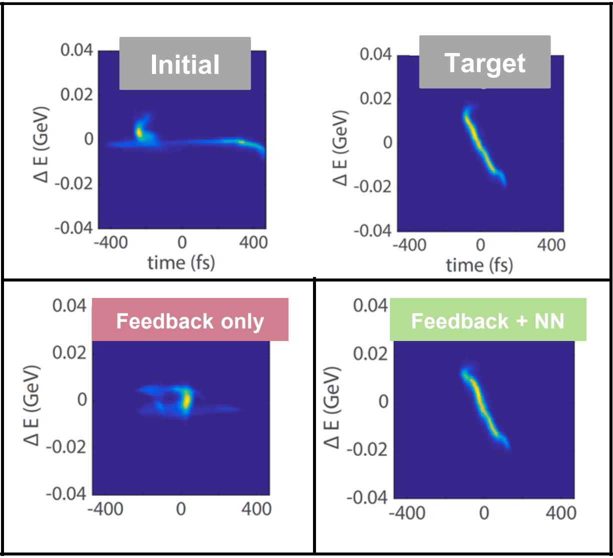


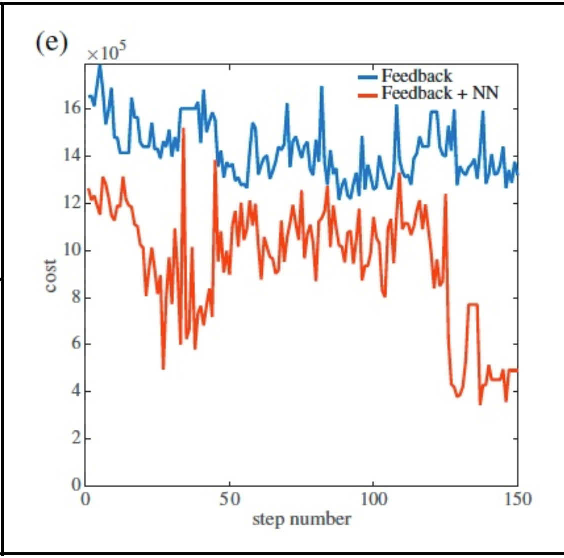
Shots are beyond the TCAV resolution

Spectral VD resolves features beyond the TCAV resolution - adds confidence bounds on ML-based prediction

ML-assisted LPS optimization



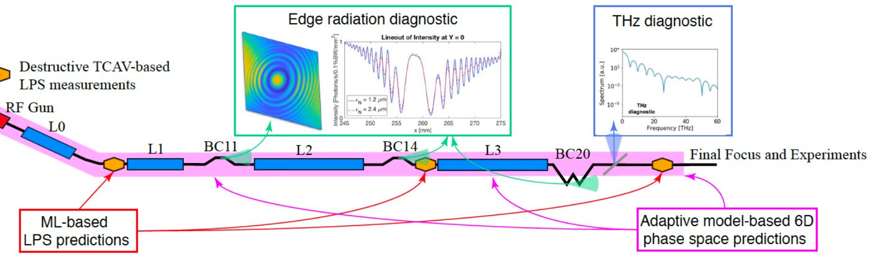




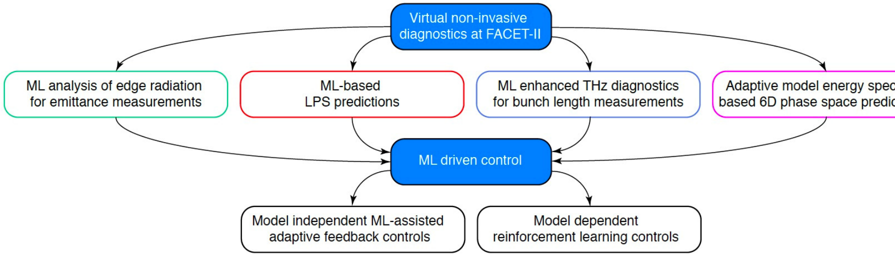
NN provides "smart" initial guess for optimizer - avoids getting stuck in local minima to converge to correct solution

Virtual Diagnostic suite for "digital twin" operation at FACET-II

FACET-II SCHEMATIC



VIRTUAL DIAGNOSTICS at FACET-II



- Virtual Diagnostics will play central role in commissioning and operation of a "digital twin" accelerator at FACET-II
- Diagnostics target multiple beam parameters (longitudinal and transverse) at multiple locations along linac (injector, bunch compressors, IP) to understand 6D phase space during transport, acceleration and beam delivery
- Diagnostic inputs work in tandem with ML-driven controls for beam delivery & customization

Conclusion and what's next

- ML-based virtual diagnostics for LPS prediction have been developed and their feasibility successfully tested.

- Successful implementation + integration with non-ML diagnostics will provide additional information for users and a signal for LPS feedback, tuning and control.

- Progress thus far has been made through a series of proof-of-concept experiments
  - **Next step** is to transition to a robust, reliable, useful tool

- **Ongoing challenges:**
  - Accurate quantification of model uncertainty
  - Retraining strategies
  - How best to combine machine + simulation data
  - Scaling to complex operation modes.

- Synergies between accelerator facilities at SLAC (and beyond) means tools developed can be broadly applicable to multiple machines and the wider community

Thank you!

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